HBMO IN ENGINEERING OPTIMIZATION

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ABSTRACT

Over the last decade, evolutionary and meta-heuristic algorithms have been extensively used as search and optimization tools in various problem domains, including science, commerce, and engineering. Their broad applicability, ease of use, and global perspective may be considered as the primary reason for their success. Honey bees mating process may also be considered as a typical swarm-based approach to optimization, in which the search algorithm is inspired by the process of real honey-bees marriage. In this paper, honey-bees mating optimization algorithm (HBMO) is presented and tested with few benchmark examples. To test the performance of the algorithm, two benchmarks constrained and/or unconstrained real valued mathematical models were selected. The algorithm application resulted in the global optimal with reasonable mating flights. To show the efficiency of the algorithm in constraint handling, the model was applied to a two-variable, two constraint highly nonlinear problem. It was shown that the performance of the model is quite comparable with the results of well developed GA. The third example is a real world water resources operation optimization problem. The developed model was applied to a single reservoir with 60 periods with objective of minimizing the total square deviation from target demand. Results obtained are quit promising and compares well with the results of some other well-known heuristic approaches.

Key words: Honey Bees Mating Optimization; GA; Mathematical Problems; Single-Reservoir Operation**.**

INTRODUCTION

Generally speaking, traditional optimization methods may be classified into two distinct groups. (1)Direct and (2)Gradient-Based methods. In direct search methods, only objective function and constraint values are used to guide the search strategy, whereas gradient-based methods use the first and/or second-order derivatives of the objective function and/or constraints to guide the search process. Since derivative information is not used, the direct search methods are usually slow, requiring many function evaluations for convergence. For the same reason, they can also be applied to variety of problems without a major change in the algorithm. On the other hand, gradient-based methods quickly converge to an optimal solution, but are not efficient in non-differentiable or discontinuous problems. In addition, there are some common difficulties with most of the traditional direct and gradient-based techniques, such as:

- The convergence to an optimal solution depends on the chosen initial solution.
- Most algorithms tend to get stuck to a suboptimal solution, with pre-mature convergence.
- An algorithm efficient in solving one optimization problem may not be efficient in solving a different optimization problem.
- Algorithms are not efficient in handling problems having discrete variables.
- Algorithms cannot be efficiently used on a parallel machine.

Over the last decade, evolutionary and meta-heuristic algorithms (EAs) have been extensively used as search and optimization tools in various problem domains. Among them genetic algorithm (GAs) and Ant Colony Optimization algorithm (ACO), have been extensively employed as search and optimization methods in various problem domains, including science, commerce, biology and engineering (Esat and Hall(1994), Gen and Cheng (1997), Wardlaw and Sharif (1999), Dorigo (1992), Dorigo and Di Caro (1999) and Jalali et al (2003)).

The behavior of honey bees is the interaction of their (1) genetic potentiality, (2) ecological and physiological environments, and (3) the social conditions of the colony, as well as various prior and ongoing interactions between these three parameters (Rinderer and Collins, 1986). Each bee undertakes sequences of actions which unfold according to genetic, ecological, and social condition of colony.

Honey-bees are also used to model agent-based systems (Perez-Uribe and Hirsbrunner 2000). In a recent work, Abbass (2001 a and b), developed an optimization algorithm based on honey bees marriage process.

In this paper a honey-bees marriage based optimization algorithm is developed and its performance is tested using three well defined and highly nonlinear benchmark mathematical functions, as well as developing an optimum operation policy for a single reservoir.

COLONY STRUCTURE

A honeybee colony typically consists of a single egg laying long-lived queen, anywhere from zero to several thousand drones (depending on the season) and usually 10000 to 60000 workers (Moritz and Southwick 1992).

Although we sometimes think of bees as simply living in “hive”, the hive is really like a big city with many “sections of the town”. A colony of bees is made up of a large family of bees living in one bee-hive. Each of the three types of bees: the queen, the drones, and the workers, have an appointed task in the hive.

The queen is the most important member of the hive because she is the one that keeps the hive going. With the help of approximately 18 males (drones), the queen bee will mate one time in her life over several days. The sperm from the drone will then be planted inside a pouch in her body. She uses the stored sperm to fertilize the eggs.

There are usually several hundred drones that live with the queen and worker bees. Mother nature has given the drones just one task which is to give the queen some sperm. After the mating process the drone die.

The marriage process represents one type of action that has proved to be difficult to study because the queens mate during their mating-flights far from the nest. A mating-flight starts with a dance performed by the queen who then starts a mating flight during which the drones follow the queen and mate with her in the air. In a typical mating-flight, each queen mates with seven to twenty drones. In each mating, sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony. Each time a queen lays fertilized eggs, she retrieves at random a mixture of the sperms accumulated in the spermatheca to fertilize the egg (Page 1980).

The queen is pursued by a large swarm of drone, “drone comets”, where copulation occurs. Insemination ends with the eventual death of the drone, and the queen receiving the “mating sign”. The queen mates multiple times but the drone inevitably only once. These features make the bees mating the most spectacular mating among insects.

HONEY BEES MODELING

The mating–flight may be considered as a set of transitions in a state-space (the environment) where the queen moves between the different states in some speed and mates with the drone encountered at each state probabilistically. At the start of the flight, the queen is initialized with some energy content and returns to her nest when the energy is within some threshold from zero or when her spermatheca is full.

A drone mates with a queen probabilistically using an annealing function as [Abbass 2001a]:

$$\Pr ob(Q,D) = e^{\frac{-\Delta(f)}{S(t)}} \quad (1)$$

where, *Prob (Q,D)* is the probability of adding the sperm of drone *D* to the spermatheca of queen *Q*; that is, the probability of a successful mating, $\Delta(f)$ is the absolute difference between the fitness of *D* (i.e. $f(D)$) and the fitness of *Q* (i.e. $f(Q)$) and $S(t)$ is the speed of the queen at time t.

Therefore a HBMO algorithm may be constructed with the following five main stages:

1. The algorithm starts with the mating–flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones). A drone is then selected from the list at random for the creation of broods.
2. Creation of new broods (trial solutions) by crossoverring the drones' genotypes with the queens.
3. Use of workers (heuristics) to conduct local search on broods (trial solutions).
4. Adaptation of workers fitness based on the amount of improvement achieved on broods.
5. Replacement of weaker queens by fitter broods.

SOLUTION REPRESENTATION (WORKING PRINCIPLE)

In the mathematical representation, a drone is represented by a genotype and a genotype marker. Realizing the fact that all drones are naturally haploid, a genotype marker may be employed to randomly mark half of the genes, leaving other half unmarked. In this case, only the unmarked genes are those that form a sperm to be randomly used in mating process.

Workers which are used to improve the brood's genotype, represent a set of different heuristics. The rate of improvement in brood's genotype, as a result of heuristic application to that brood, defines the heuristic fitness value. As an example, in one point crossover heuristic, the crossover heuristic operator applies to the brood's genotype with that of a randomly generated genotype where the crossover point is also selected at random.

The queens play the most important role in the mating process in nature as well as in the HBMO algorithm. Each queen is characterized with a genotype, speed, energy, and a spermatheca with defined capacity. Spermatheca is defined as a repository of drones' sperm after mating process with queen. Therefore, for a queen with defined spermatheca size, speed, and energy are initialized before each mating flight, at random in the range of (0.5, 1). Since the drones' are assumed to be haploid, after successful mating, the drones' sperm is stored in queens' spermatheca. Later in breeding process, a brood is constructed by copying some of drones' genes into the brood genotype and completing the rest of the genes from the queens' genome. The fitness of the resulted genotype is determined by evaluating the value of the objective function of the brood genotype and/or its normalized value. It is important to note that a brood has only one genotype.

Algorithm Application

To test the performance of the proposed algorithm, the model was applied to a few benchmark constrained and unconstrained mathematical optimization functions.

Unconstrained optimization deals with the problem of minimizing or maximizing a function in the absence of any restrictions.

The first numerical example of unconstrained optimization problem is given as follows [Gen and Cheng (1997)]:

$$\text{Maximize } f(x_1, x_2) = 21.5 + x_1 \sin(4\pi x_1) + x_2 \sin(20\pi x_2) \tag{2}$$

$$-3.0 \le x_1 \le 12.1 \tag{3}$$

$$4.1 \le x_2 \le 5.8 \tag{4}$$

Employing the proposed HBMO algorithm, the best fitness value was obtained as of 38.850293 with average over 10 runs of 38.850290, indicating a very small standard deviation (Table (1)). The best, worst, and average rate of convergence for 10 runs is presented in Figure (1).

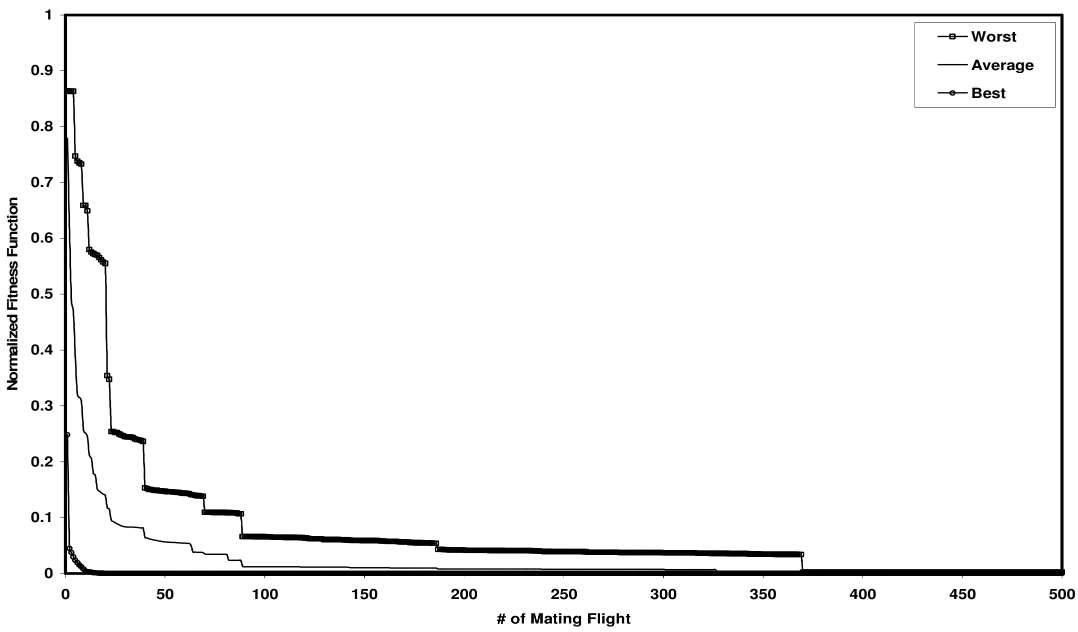

Figure 1. Rate of convergence of first example problem for 10 runs

To show the efficacy of this handling method, we apply GAs with this method to solve a two-variable, two-constraint NLP problem:

$$\text{Maximize } f1(x_1, x_2) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2 \tag{5}$$

Subject to:

$$g_1(x) \equiv 5.059 - x_1^2 - (x_2 - 2.5)^2 \geq 0 \tag{6}$$

$$g_2(x) \equiv (x_1 - 0.05)^2 + (x_2 - 2.5)^2 - 4.84 \geq 0 \tag{7}$$

$$0 \leq x_1 \leq 6 \quad 0 \leq x_2 \leq 6 \tag{8}$$

Employing the same algorithm with, the average fitness value over 10 runs was obtained as $f(x^*, x^*) = 13.628688$, with the best result as low as 13.59084 units. More details are provided in Table (1). Figure (2) shows how the HBMO solutions converge to a very close feasible solution or to the true optimum solution for 10 different runs.

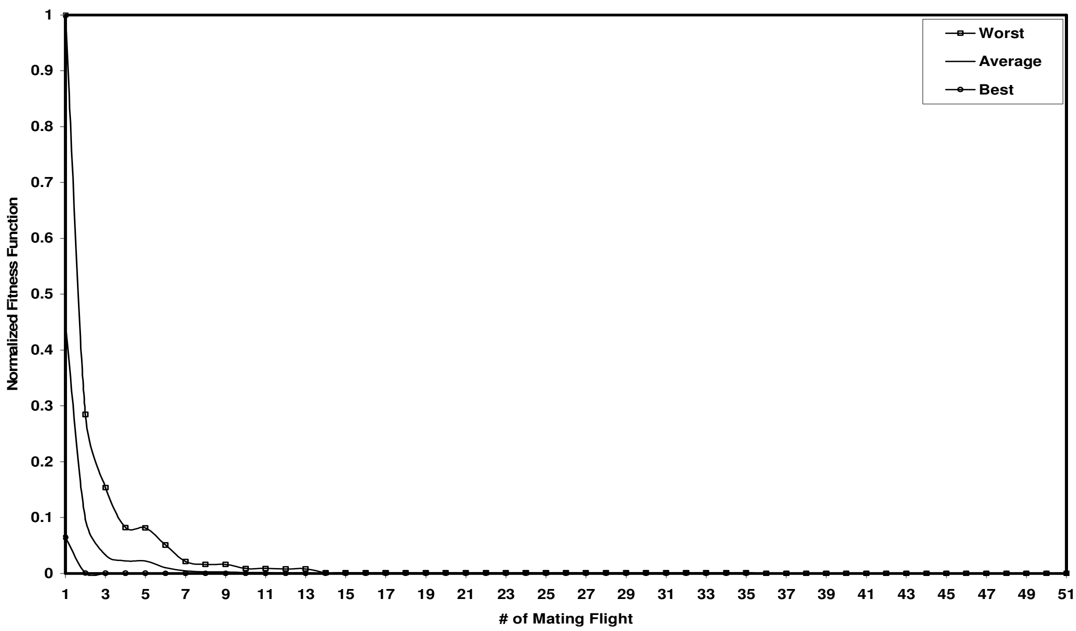

Figure 2. Rate of convergence of second example problem for 10 runs

SINGLE RESERVOIR OPERATION OPTIMIZATION

The third example is a real world problem which deals with optimum operation of Karkheh reservoir in IRAN. The objective of the study is defined as minimum total squared deviation of release from target demand.

$$\text{Minimize TSD} = \sum_{t=1}^{nt} (R_{(t)} - D_{(t)})^2 \qquad (9)$$

Data used in this case example is provided elsewhere (Bozorg Haddad and Afshar (2004)).

Results of the model for storage volume at the end of each period are presented in Figure (6). For the same problem, along with the global optimum, monthly release resulted from the HBMO model with 50 mating flights (or iteration) is presented in Figure (7). Monthly demand and the global optimum results are presented in the same figure. In order to have a notion of the rate of convergence of the model, Figure (8) is presented. Very rapid convergence, as well as comparable total squared deviation from the target demands makes the approach and algorithm quite promising for further development and application in the field of water resources planning and management.

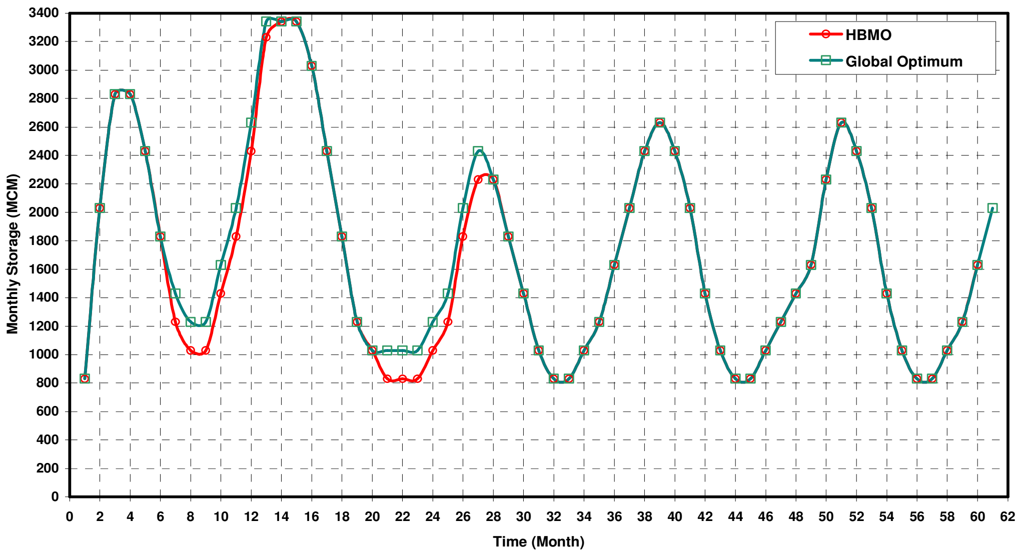

Figure 3. Storage volume at the end of each period

Table 1. Results of three different problems, with their statistical measures

Example Number	Spermatheca Size	Max No. of Mating Flight	Best Fitness Value	Worst Fitness Value	Average Over 10 Runs	Standard Deviation
1	300	1000	13.782440	13.590840	13.628688	.079275
2	300	500	38.850300	38.850290	38.850294	.000005

Table 2. Results of ten different runes, with their statistical measures in reservoir operation problem

Iteration number	1	2	3	4	5	6	7	8	9	10	Mean	Min.	Max.	Standard Deviation	Coefficient of Variation
HBMO	1.32	1.34	1.14	1.27	1.28	1.14	1.43	1.10	1.24	1.34	1.26	1.10	1.43	0.11	.084
Global Optimum	1.07														

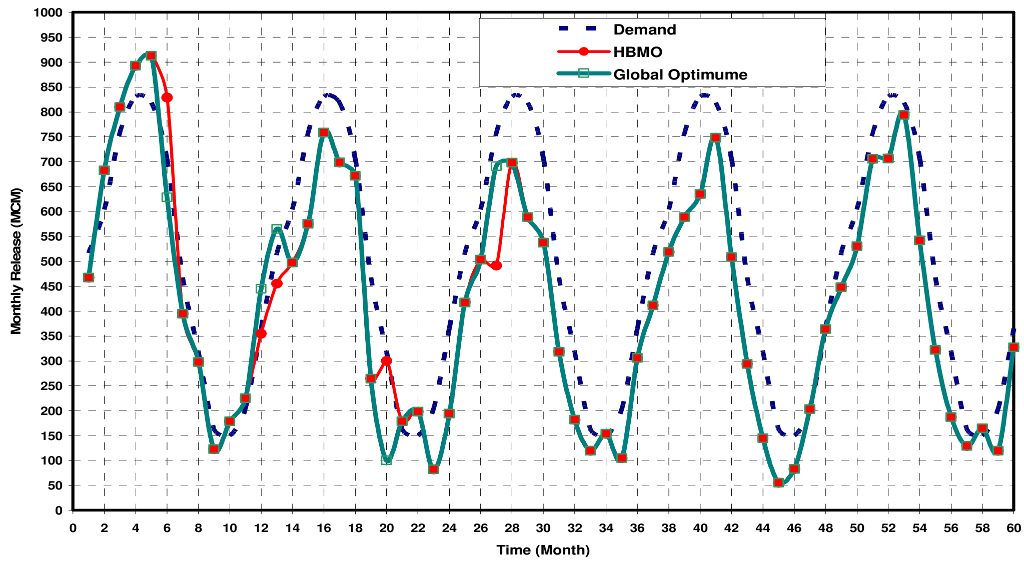

Figure 4. monthly release resulted from HBMO model and global optimum

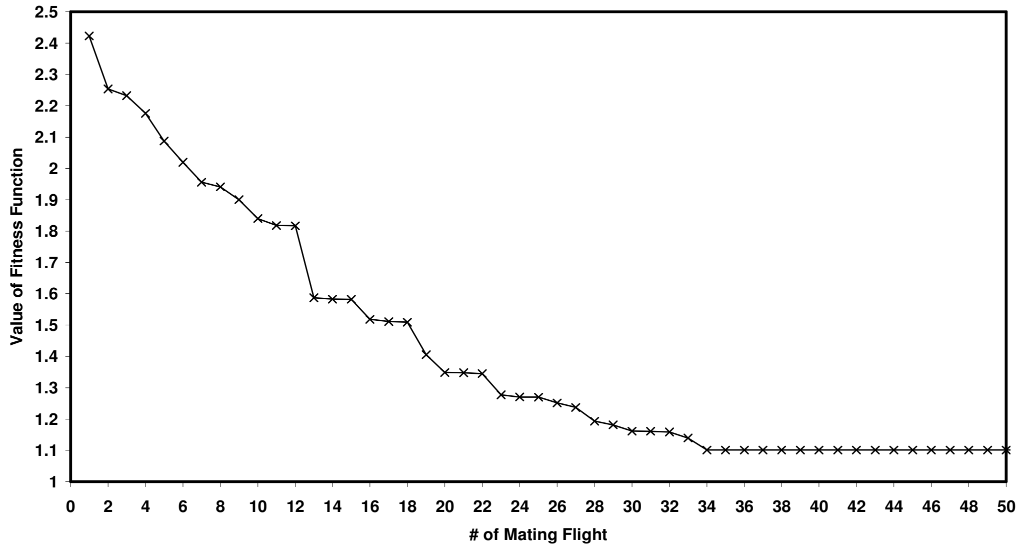

Figure 5. Rate of convergence of the model in reservoir operation problem

Results of 10 different runes, with their statistical measures along with the global optimum are presented in Table (2).

CONCLUDING REMARKS

Modeling honey bees marriage process as an optimization algorithm and its application to few benchmarks, highly nonlinear-constrained and/or unconstrained optimization problems, such as well known Ackley's function, partially reveals the high potential of the proposed algorithm to solve nonlinear optimization problems. Preliminary results obtained from the model application compared very well with those resulted from similar heuristic methods as well as global optimum results.

NOTATIONS

$\Pr ob(Q,D)$	Probability of adding the sperm of drone *D* to spermatheca of queen *Q*
$\Delta(f)$	Absolute difference between the fitness of *D* (i.e. *f*(*D*)) and the fitness of *Q* (i.e. *f*(*Q*))
$S_{(t)}$	Speed of the queen at time *t*
α	Factor of speed reduction after each transition (0,1)
$E(t)$	Energy of the queen at time *t*
γ	Amount of energy reduction after each transition
TSD	Total Square Deviation of release from demand in each operation time
$R_{(t)}$	Release from dam in period *t*
$D_{(t)}$	Demand in period *t*

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